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A Review on Artificial Intelligence and Machine Learning Techniques for Neurological Disorder Diagnosis: Challenges, Biases and Clinical Considerations

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ABSTRACT

The brain functions as the central control centre of the body and a growing number of novel neurological disorders are being recognized. The wide range of brain illnesses presents challenges for existing diagnostic and detection technologies, making it a persistent area of research. Effective treatment for neurological illnesses depends on early identification. The accuracy of predicting and diagnosing these illnesses has greatly increased with the use of artificial intelligence in medicine. Neurological diseases (ND) are increasingly affecting individuals across all age groups, including children, adults, pregnant women, parents, and even healthy infants. These disorders vary in their origins, symptoms, outcomes, and prognoses. Neuroimaging techniques such as MEG, MRI, and PET have shed light on brain function in recent years. These developments provide encouraging prospects for using computer-assisted diagnostic tools in conjunction with diverse machine learning and deep learning methodologies to diagnose neurological disorders. Our study is centered around discovering various ML/DL approaches that can be used to detect and classify neurological disorders, such as Alzheimer's disease, multiple cerebral palsy, Parkinson's disease, sclerosis, epilepsy, and brain tumours. We are especially interested in techniques that can detect these disorders at an early stage. This review explores the breadth of ML and deep learning (DL) techniques employed for diagnosing neurological conditions. We examine key datasets, model architectures, performance benchmarks, and highlight major gaps including data imbalance, lack of multimodal standardization, and demographic underrepresentation. Furthermore, we address the ethical and regulatory challenges tied to clinical deployment, such as patient privacy, algorithmic bias, and FDA compliance. The review concludes with future directions emphasizing explainable AI, federated learning, and clinical validation pathways.

Keywords: *Neurological disorders, Deep Learning, Machine Learning, Ethical AI, Dataset bias, Regulatory AI, Neurodiagnostics*

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1. INTRODUCTION

Neuropathies (ND) are a class of disorders characterized by brain dysfunction. Neurological diseases, also known as brain, behavioral or cognitive disorders, impair functions such as walking, learning, speaking and movement. When the brain, the body's central control unit, is affected, it can pose life-threatening risks. Awareness of these disorders helps reduce fatality rates, though some may lead to permanent or partial impairment. Globally, these conditions account for 10.2% of cases, rising to 16.8% annually [1]. Studies show that neurological and neuropsychiatric disorders cause higher impairment rates compared to other illnesses. Research on neurological disorders is still in its early stages, presenting various challenges. Algorithms and models from machine learning form the basis of computer-aided diagnosis systems. Data pre- processing, feature extraction, and classification are the components shown in Figure 1 of CAD systems. CAD tools allow experts to analyze large clinical datasets, reducing diagnosis time and improving accuracy. These systems are cost-effective and efficient, supporting professionals in diagnosing and treating neurological disorders. Medical records and other clinical data undergo processing in CAD methods to lessen computational complexity and noise. A key component of CAD systems is their extraction mechanism, which isolates disease biomarkers. Classification models take the retrieved data as input and label people as healthy or abnormal based on the CAD results. As the brain's central role continues to be understood, more neurological disorders are being discovered, complicating diagnosis. Early diagnosis plays a crucial role in improving treatment. Artificial intelligence (AI) is becoming more integrated into science and enhances the accuracy of predicting and diagnosing neurological disorders.

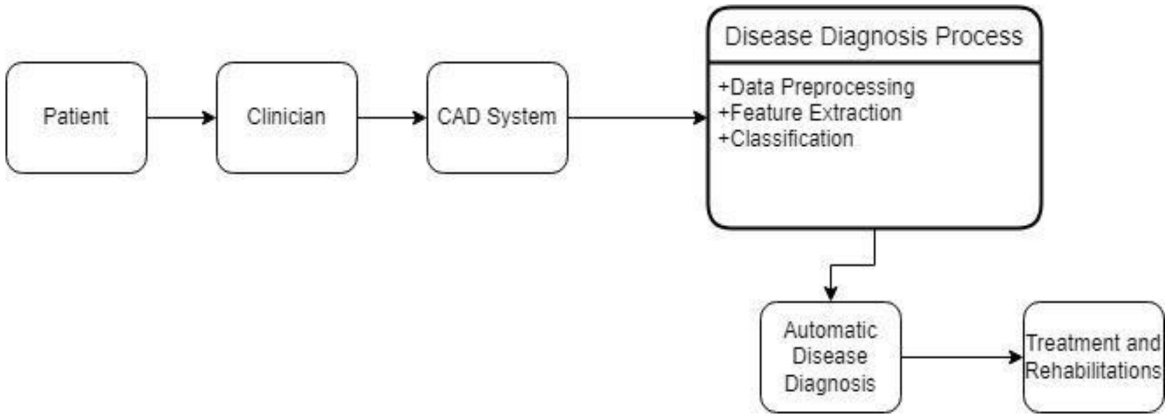

Figure 1: Architecture of Computer-aided diagnosis (CAD) system [1]

The application of AI in neurology is an extrapolation of successes made in other general areas of medicine, where large datasets have been analyzed by machine learning algorithms, neural networks, and other AI technologies to help predict outcomes and guide clinical decision-making [45]. Various sections of the paper are structured as outlined below: Section 2 describes the literature survey and Comparative Analysis of ML/DL algorithms used for Neurological diseases. Section 3 provides a broad description of the dataset. Section 4 provides different types of Neurological diseases information in which research is needed. Section 5 discusses the methods and procedures for pre-processing. Section 6 elaborates the feature extraction technology for ND diagnosis. Section 7 encompasses the primary varieties of deep learning and machine learning techniques. Section 8 addresses the unresolved challenges and future direction for researchers and Section 9 concludes the paper.

2. LITERATURE SURVEY

This part will examine the various neurological diseases and how deep learning and machine learning approaches compare and contrast. To distinguish between people with Parkinson's disease and healthy controls, Mohamad Alissa et al. (2022) investigated the application of convolution neural networks (CNNs), an architecture of deep neural networks. The goal was to advance Parkinson's research by employing creative methods to analyze patient resistance configurations. The study specifically examined the effectiveness of two drawing tasks linear rays and spiral pentagons, in recognizing Parkinson's disease (PD). With a 93.5% success rate, the CNN classifier was able to analyse the pentagon drawings, proving that this technology is ideal for use in point-of-care diagnostic instruments. Deep recurrent neural networks (RNNs) and other alternative deep learning models could be explored in future studies for longitudinal patient data analysis. A further notable study, Mahmood Saleh Alzubaidi et al. (2021) conducted an evaluation of 91 studies from a total of 1061 that satisfied the inclusion criteria. This review emphasised the utilisation of neural networks in diagnosing Parkinson's disease, concentrating on gait patterns (freezing of gait), speech data, and biological signals, especially from MRI scans. The researchers underscored the significance of brain connection in the detection of Parkinson's disease. Using convolution neural networks and MRI data, Qiu et al. (2019) classified patients with schizophrenia in a separate investigation. After applying spatial normalization and motion correction to the data, the authors classified the results using 2D-CNNs. They were able to get a classification accuracy of 72.35% in the AUD and 72.60% in the DNN using their method. A sensitivity rate of 79% and a specificity rate of 80% were recorded by the DMN, suggesting that CNNs were effective in schizophrenia classification. Finally, Deep Belief Networks (DBNs) were used to detect seizures using electroencephalogram (EEG) by Xuye1 et al. (2017) Beyond competing learning models like auto encoders, artificial neural networks and support vector machines, their model attained an accuracy of more than 90%. When it came to identifying spikes in seizures, the DBN model was much more sensitive and specific. Using age, medical visit frequency, Mini-Mental State Examination (MMSE) scores, and educational attainment as psychological variables, Neelaveni and Devasana (2020) trained machine learning algorithms to predict the onset of Alzheimer's disease. One of the most important indicators of prognosis is the MMSE score. The disease-related characteristics the model prioritized over data discrepancies were age, MMSE score, number of visits, and education level. Decision trees and support vector machines (SVMs) are examples of machine learning algorithms that led to 83% and 85% prediction accuracies, respectively. The majority of the dataset, around 70%, was utilised for training, while the remaining 30% was reserved for testing. Future studies that combine brain MRI imaging with mental health data may improve the precision and timeliness of Alzheimer's predictions. Similarly, Palraj and Siddan (2021) used deep learning methods to image and diagnose cerebral palsy in infants. This study successfully classified certain forms of cerebral palsy using MRI images of children's brains processed by a deep convolution network based on a modified AlexNet architecture. The network achieved an accuracy of 76.8%. Rehabilitation strategies and results for children with cerebral palsy may be significantly enhanced by adopting this strategy. This literature review synthesizes key findings on ML/DL model performance across modalities and disorders. However, these promising results are often hampered by issues such as small or skewed datasets, modality inconsistency, and limited external validation. This paper addresses these gaps and outlines recommendations for future research.

2.1 Comparative Analysis of ML/DL algorithms used for Neurological diseases

Table 1: Comparative Analysis of ML/DL algorithms used for Neurological diseases

S. No.	Paper Title and Disease	Dataset	Model Used	Conclusion	Research Gap/ Future Work
1	Parkinson's Disease[16]	87 individuals (58 patients, 29 healthy controls).	Convolution Neural Network (CNN) to distinguish Parkinson's patients through sketching tasks.	Achieved 93.5% accuracy from pentagon drawing task.	Explore deep learning models like RNNs to analyze time-series data and assess dynamic patient movements.
2	Multiple Sclerosis[39]	72 individuals with MS and 59 healthy controls.	Exemplar Multiple Parameter LPQ (ExMPLPQ) combined with Fine k-NN for binary classification.	Achieved 98.37%, 97.75%, and 98.22% accuracy in axial, sagittal, and hybrid datasets, respectively.	Future studies to include more brain MRI datasets and diseases like migraines and vasculitis to improve model generalization.
3	Alzheimer's Disease[13]	MMSE score, age, frequency of visits, and patient education were used.	Support Vector Machine (SVM) and Decision Tree models.	Achieved 85% accuracy with SVM and 83% with Decision Tree models.	Future studies should integrate brain MRI images with psychological data to enhance early detection accuracy.
4	Epilepsy[40]	Scalp EEG dataset from CHB-MIT of 24 participants, aged 2-22 years.	CNN for feature extraction and SVM for classification.	Achieved sensitivity of 92.7% and specificity of 90.8%.	Further preprocessing to improve the signal-to-noise ratio, and deep learning methods may be explored with reduced parameters for more efficient models.
5	Parkinson's Disease[18]	Datasets derived from biomedical signal and speech datasets from Google Scholar, IEEE, ACM, ScienceDirect, PubMed.	Scoping review of neural networks in Parkinson's disease diagnosis.	Reviewed 91 studies. 50% of included studies utilized neural networks, highlighting their effectiveness in diagnosing Parkinson's disease.	Use MRI and CT scan images in combination with speech datasets to further enhance the diagnosis capabilities.

6	Parkinson's Disease[20]	Data from Parkinson's Disease Progression Markers Initiative (PPMI) database.	Deep learning model applied using premotor characteristics (REM, olfactory loss, cerebrospinal fluid data).	Achieved 96.45% accuracy outperforming 12 machine learning and ensemble learning models.	As datasets grow, further explore deep learning's potential and capabilities for Parkinson's diagnosis.
7	Alzheimer's Disease[11]	OASIS and Kaggle datasets containing MRI data for Alzheimer's.	XGBoost, Random Forest, Decision Tree, SVM, Voting Classifier with 5-fold cross-validation.	Achieved an average accuracy of 83%.	Future studies should focus on feature elimination and extraction to further improve detection accuracy, integrating clinical measures like MMSE and education levels.
8	Parkinson's Disease[41]	Neuro Imaging Informatics Technology Initiative (NIfTI) data in non-flair (T2-weighted) greyscale axial 3D MR images.	2D and 3D CNN models with N4 bias correction, histogram matching, z-score normalization, and scaling techniques.	3D CNN model achieved 88.9% accuracy (AUC 0.86) compared to 2D CNN's 72.22% accuracy (AUC 0.50).	Future work includes using larger datasets, GPU parallelization, and multi-model input (e.g., MRI + SPECT) to enhance diagnostic accuracy for Parkinson's disease.
9	Parkinson's Disease[42]	Audio recordings of 42 early-stage Parkinson's patients (5875 recordings).	Ensemble of top 5 machine learning models: KNN, Random Forest, Bagged MARS, Project Pursuit Regression, and Boosted GLM.	Achieved 99.6% accuracy in predicting motor Unified Parkinson's Disease Rating Score (UPDRS).	Expand dataset with voice samples in different languages to improve model's ability to predict dysprosody progression in Parkinson's over time.
10	Alzheimer's Disease[12]	2D and 3D convolutional MRI dataset from Alzheimer's Disease Neuroimaging Initiative (ADNI).	CNN architectures for 2D and 3D classifications, with transfer learning using the VGG19 model.	Achieved 93.61% accuracy for 2D classification and 95.17% for 3D classification; 97% with fine-tuned VGG19 model.	Future work will focus on testing EfficientNet B0 to B7 models and applying MRI segmentation to improve Alzheimer's stage detection accuracy.
11	Parkinson's Disease [46]	328 subjects (187 PD, 141 healthy controls); Smartphone accelerometer and gyroscope data from walking tests	CNN-LSTM hybrid architecture processing time-series sensor data; Feature extraction from gait patterns	Achieved 93.7% accuracy, 92.1% sensitivity, 95.4% specificity; Demonstrated feasibility of unobtrusive PD monitoring via everyday devices	Limited data from advanced PD stages; Need for longitudinal validation; Integration with other biomarkers could improve early diagnosis

12	Alzheimer's Disease[47]	ADNI dataset: 754 subjects across healthy, MCI, and AD; T1-weighted MRI, fMRI, and DTI scans	Graph neural network constructed from brain connectivity data across modalities; Attention mechanism to weigh different imaging biomarkers	91.2% accuracy in classifying AD vs. healthy; 87.3% for early MCI detection; Identified key structural and functional connectivity patterns	Limited ethnic diversity in ADNI dataset; Need for external validation across populations; Integration with non-imaging biomarkers
13	Epilepsy[48]	CHB-MIT dataset with 916 hours of continuous EEG recordings from 23 pediatric subjects; Complemented with ECG data	Wavelet transform for feature extraction; Transformer-based model for temporal sequence analysis; Fusion of EEG and ECG features	96.8% accuracy in seizure detection; 88.5% accuracy in classifying 5 seizure types; Average detection latency of 3.1 seconds	Real-time implementation challenges; Need for validation on low-resource hardware; Personalization for individual seizure patterns
14	Cerebral Palsy[49]	187 children (112 with CP, 75 controls); 3D video recordings of standardized movement tasks	Deep learning-based pose estimation (OpenPose extension); Quantification of movement asymmetry and variability; Temporal trajectory analysis	89.3% accuracy in CP classification; Identified distinct movement patterns across different CP subtypes (spastic, dyskinetic, ataxic); Correlation with clinical assessment scales (r=0.79)	Limited to controlled clinical settings; Integration with wearable sensors needed; Expansion to free-living activity assessment
15	Multiple System Atrophy (MSA)[50]	203 subjects (87 MSA-P, 62 MSA-C, 54 controls); DaT-SPECT imaging, MRI volumetric data, and clinical assessments	Ensemble of CNNs for imaging data; Integration with tabular clinical data using gradient boosting; Transfer learning from Parkinson's models	90.7% accuracy in MSA detection; 85.3% accuracy in MSA-P vs MSA-C differentiation; AUC of 0.93 for detection	Small sample size; Difficulty in early-stage diagnosis; Need for molecular biomarker integration; Longitudinal progression modeling
16	Progressive Supranuclear Palsy (PSP)[51]	167 participants (89 PSP, 78 controls); High-speed eye-tracking during saccade and pursuit tasks	CNN processing temporal eye movement signals; Attention mechanisms to identify diagnostically relevant movement segments	92.1% accuracy in PSP detection; Early detection possible (avg. 16 months before clinical diagnosis); 87.6% specificity vs. other parkinsonian syndromes	Limited validation against MSA and CBD; Need for combination with neuroimaging; Wearable implementation for continuous monitoring

17	Epilepsy[52]	TUH Epilepsy Corpus with 2,993 recordings from 783 subjects across 7 hospitals	Federated learning approach with local CNN-RNN models; Secure aggregation protocol; Knowledge distillation for model compression	92.4% accuracy without sharing raw patient data; Reduced institutional bias; 3.8 second average detection latency	Communication overhead in resource-constrained settings; Model heterogeneity across institutions; Handling concept drift over time
18	Alzheimer's Disease [53]	1,420 subjects from 5 memory clinics; MRI, PET, CSF biomarkers, cognitive assessments	Explainable boosting machines with interpretable feature interactions; Shapley values for feature importance	94.1% accuracy in AD vs. other dementias; Identified novel biomarker combinations; Personalized risk stratification	Limited validation in diverse ethnic groups; Integration with genetic biomarkers; Need for longitudinal progression markers
19	Parkinson's Disease [54]	PPMI dataset: 619 subjects (388 PD, 231 controls); DaTscan SPECT images	Transfer learning from ImageNet; Siamese networks for contrastive learning with limited labeled data	95.2% accuracy in PD detection; Effective with 40% less labeled data; AUC of 0.97	Limited to research-grade imaging; Need for multimodal integration; Validation in prodromal phases
20	Parkinson's Disease (Freezing of Gait)[55]	48 PD patients with freezing of gait; Continuous 7-day monitoring with wearable accelerometers	Attention-based RNN processing time-series data; Detection of gait irregularities in free-living conditions	87.3% real-time detection accuracy; 91.2% for post-hoc analysis; Classification of 5 freezing subtypes	Battery life limitations for continuous monitoring; Need for integrated intervention systems; Personalization for individual gait patterns
21	Epilepsy[56]	218 subjects with 1,650 nights of sleep EEG recordings; Mix of focal and generalized epilepsy	Transformer architecture for temporal sequence analysis; Self-supervised pre-training on unlabeled sleep data	89.7% accuracy in seizure prediction from sleep patterns; Identified novel sleep biomarkers of seizure susceptibility	Limited to research-grade EEG; Need for consumer-grade devices; Integration with circadian rhythm data
22	Alzheimer's Disease[57]	512 subjects (189 AD, 162 MCI, 161 controls); Standardized speech tasks and natural conversations	Self-supervised learning on large speech corpus; Fine-tuning on linguistic and acoustic features	84.3% accuracy in AD detection from speech; 79.1% for MCI detection; Correlation with cognitive assessment scores (r=0.74)	Need for longitudinal validation; Culturally and linguistically diverse validation; Integration with other cognitive biomarkers
23	Multiple System Atrophy (MSA)[58]	176 subjects (89 MSA, 87 controls); T1-weighted and diffusion MRI	3D graph neural network capturing structural connectivity;	88.9% accuracy in MSA detection; 83.6% accuracy in differentiating from	Small sample size; Need for longitudinal progression

			Regional atrophy patterns as node features	Parkinson's; Identified novel structural biomarkers	models; Integration with clinical variables
24	Cerebral Palsy[59]	132 children with CP (varying GMFCS levels); Smartphone-based assessment of reaching tasks	CNN processing video data; Quantification of movement quality from common smartphone camera	85.7% agreement with clinical GMFCS assessment; Remote monitoring capability; Identification of therapy response indicators	Limited to upper limb assessment; Need for whole-body analysis; Validation in home environments
25	Progressive Supranuclear Palsy (PSP)[60]	201 subjects (93 PSP, 108 controls); MRI, clinical assessments, and motor examinations	Deep multimodal fusion network; Separate encoding pathways for imaging and clinical data	91.5% accuracy in PSP detection; 87.2% in distinguishing from Parkinson's; Earlier detection than clinical diagnosis alone	Limited sample size; Need for validation in early-stage cases; Integration with molecular biomarkers

3. DATASET

Discussions or evaluations related to diagnosing and treating neuropathy often focus on techniques, protocols, and outcomes. Therefore, for better assessment of diagnostic tools and methods, a variety of datasets pertaining to neurological diseases are deemed essential. Classifications are the usual means by which these datasets are arranged. Brain problems are often diagnosed using MRI pictures and recordings. Magnetic resonance imaging (MRI) is a non-invasive technique that facilitates the visualisation of brain anatomy, assessment of abnormalities, diagnosis of conditions, and formulation of treatment strategies. Different MRI modalities are employed to detect, define, and categorize brain disorders and anomalies. A notable category encompasses electroencephalographic (EEG) recordings, which document electrical impulses in the brain. EEG measurements reflect the brain's electrical activity and may signify disturbances in neuronal function.

The examination of EEG signals is essential for the diagnosis and monitoring of neurological disorders, including epilepsy and autism spectrum disorder (ASD). Additionally, remote diagnostic models for predicting Parkinson's disease and remote monitoring systems that assess speech patterns have gained prominence. A collection of audio recordings featuring syllables, words, and phrases spoken by individuals with Parkinson's disease has been developed for analysis. The table2 below provides links to datasets and information on conditions such as Alzheimer's disease, cerebral palsy, Parkinson's disease, brain tumours, epilepsy, and others [1].

Table 2: Table for dataset of different Neurological Disorders (ND) for different modalities

S. No.	Modality	Disease	Database Name	Link
1	EEG	Epilepsy	Bonn Time Series Database	https://repositori.upf.edu/handle/10230/42894
2	EEG	Epilepsy	Temple University EEG Corpus	https://isip.piconepress.com/projects/tuh_eeg/html/downloads.shtml
3	MRI	Alzheimer's disease	Open Access Series of Imaging Studies (OASIS) 1	https://www.oasis-brains.org/
4	EEG	Epilepsy	Neurology and Sleep Centre, New Delhi EEG Database	https://www.researchgate.net/publication/308719109_EEG_Epilepsy_Datasets
5	MRI	Alzheimer's disease	Alzheimer's Disease Neuroimaging Initiative	http://adni.loni.usc.edu/about/

			(ADNI)	
6	Handwriting	Parkinson's disease	Spiral Dataset (UC Irvine Machine Learning Repository)	https://archive.ics.uci.edu/ml/datasets/Parkinson+Disease+Spiral+Drawings+Using+Digitized+Graphics+Tablet
7	MRI	Brain tumour	Brain MRI Images for Brain Tumour Detection	https://www.kaggle.com/navoneel/brain-mri-images-for-braintumor-detection
8	MRI	Brain tumour	Br35H: Brain Tumour Detection 2020	https://www.kaggle.com/ahmedhamada0/brain-tumor-detection
9	MRI	Brain tumour	Brain Tumour Dataset	https://figshare.com/articles/dataset/brain_tumor_dataset/1512427
10	MRI	Brain tumour	BraTS 2019	https://paperswithcode.com/dataset/brats-2019-1
11	MRI and PET	Alzheimer's disease	OASIS 3	https://www.oasis-brains.org/
12	NA	Cerebral Palsy	Dataset Cerebral Palsy Pre- and Post-Botulinum Toxin A	https://figshare.com/articles/dataset/Dataset_cerebral_palsy_pre_and_post_Botulinum_Toxin_A\/2055729
13	Speech Recordings	Parkinson's disease	Parkinson's Telemonitoring Voice Dataset	https://archive.ics.uci.edu/ml/datasets/parkinsons+telemonitoring
14	Speech Recordings	Parkinson's disease	Parkinson's Disease Classification Dataset	https://archive.ics.uci.edu/ml/datasets/parkinsons
15	Ultrasound Images	Parkinson's disease	Shanghai East Hospital of Tongji University (TCS Dataset)	https://www.aimspress.com/article/doi/10.3934/mbe.2019280?viewType=HTML

4. NEUROLOGICAL DISEASES

Conditions affecting the brain and spinal cord are referred to as neurological disorders. Common symptoms include weakness, muscular cramping, fatigue, paralysis, coordination issues, and memory loss. Brain tumours, PD, dementia, MS, migraines, epilepsy, AD, brain traumas, and strokes are just a few of the more than 600 disorders that can impact the brain. The usual goal of a neurological examination is to detect unusual or uncommon neurological disorders.Brain diseases such as epilepsy, Alzheimer's disease, mental illness, cerebral palsyand Parkinson's disease are among the many neurological conditions that this study aims to examine in depth using deep learning and machine learning techniques [2].

4.1 Parkinson's disease (PD)

After Alzheimer's disease, Parkinson's disease ranks high among neurodegenerative illnesses. Symptoms including bradykinesia (slowed movement), rest tremor (shaking, particularly in the hands), and muscular stiffness (restricted normal movement) are hallmarks of this condition. A quicker diagnosis can be made by keeping an eye on these signs. These early symptoms can be used to construct machine learning (ML) algorithms that can detect Parkinson's disease [2]. PD manifests as a chronic neurodegenerative condition with motor impairments, sensory disturbances, depression, and pain. It affects between 4.5 to 19 per 100,000 people annually [4], occurring across both sexes and all age groups. For a long time, motor symptoms were the main indicator of Parkinson's disease. Although clinical trials have examined these main indicators extensively, many disease severity markers have not. Due to their lack of specificity, non-motor symptoms, which many people experience before Parkinson's disease begins, are notoriously difficult to diagnose and assess. Some of these symptoms include changes in sensation and changes in cognition (attention, planning, etc.). While non-motor symptoms alone cannot provide a definitive diagnosis, they contribute to the overall assessment. The utilisation of machine learning methods to improve the diagnosis of Parkinson's disease is increasing. Machine learning enables computers to autonomously learn and identify significant patterns in data with minimal human intervention. Machine learning models for diagnosing Parkinson's disease have utilised data from several sources, including movement, speech, cerebrospinal fluid (CSF), blood, and optical coherence tomography (OCT). To further enhance diagnosis accuracy, machine learning can integrate data from many approaches, such as SPECT and MRI scans. These methods enable the early or atypical diagnosis of PD by identifying key factors that are not always considered in traditional diagnostic processes [5].

4.2. Schizophrenia:

Disruptions in thought processes, feelings, and actions brought on by structural and functional abnormalities in the brain characterize schizophrenia (SZ), a severe mental illness. Using DL approaches and MRI data, numerous researchers have been working on tools and strategies for early SZ diagnosis in recent years [3].

4.3. Cerebral palsy:

The neurological condition known as cerebral palsy usually manifests in early childhood or infancy and causes a lifelong disability in motor control and coordination of muscles.These impairments in movement, body control, and balance result from brain damage due to trauma or developmental abnormalities. The condition affects the cerebral cortex, the part of the brain responsible for controlling muscle movement. In their study, Zhang et al. [1]used supervised machine learning methods to classify sagittal gait patterns in children with spastic diplegia, a form of cerebral palsy.

4.4. Epilepsy

Common symptoms of epilepsy include behavioural changes, memory problems, body weakness, and difficulties with recollection. Epilepsy affects an estimated 39 million people worldwide, with men being the most frequently affected [23]. Cognitive decline and memory loss are hallmarks of Alzheimer's disease (AD), which causes a steady loss of motor control and eventually mortality in affected patients. Traditionally, radiologists manually monitored the progression of Alzheimer's disease through its stages, but these manual methods posed significant risks to patients. Recent developments in DL and ML have made early AD detection possible, which has improved patient outcomes [2].

4.5. Brain Tumour

Because brain tumours are so lethal, early diagnosis is of the utmost importance in this day and age. Brain tumours, which can be benign or malignant, develop when cells in the brain grow abnormally. The varying appearance of different brain tumours complicates their diagnosis. Additionally, removing tumours from certain areas of the brain presents a significant challenge [2].

5. PREPROCESSING TECHNOLOGY FOR DIAGNOSIS OF NEUROLOGICAL DISEASES

Preprocessing is essential to prepare experimental data for statistical analysis. Noise factors such as variability in location, average signal intensity, and motion can distort brain imaging signals. It is critical to clean the data of artefacts and noise to guarantee reliable analysis. Below are some common methods used to preprocess neural datasets for analysis.

5.1 Normalization (NM):

Normalization in imaging is similar to adjusting or standardizing data. It involves reshaping and resizing data to align with anatomical models. By comparing various MRI scans of the brain, normalization adjusts them to a common scale and format. This process converts data from different sources into a standard reference, often using charts and models. In deep learning, image normalization typically involves zero mean and unit variance. Several methods for achieving normalization include numerical normalization, statistical parametric mapping (SPM), intensity normalization, spatial normalization, and the advanced normalization tool (ANT). Examples of normalization techniques include spatial normalization, intensity normalization, z-score normalization, and numerical normalization (NNM).

5.2 Filter:

A filter is a technique used to modify or enhance an image by applying an algorithm to pixel values near the corresponding input pixel. In image processing, filters are commonly used to smooth out high-frequency components or reduce certain frequencies to highlight or detect edges. Various filtering techniques include temporal filtering (TF), Wiener filtering (WF), spatial filtering (SF) and high-pass filtering (HPF) [1].

5.3. Smoothing:

The smoothing process helps reduce image noise by lowering the density of image pixels. Spatial smoothing (SS) is achieved by averaging the values of neighboring voxel markers. While this improves the signal-to-noise ratio (SNR), it also darkens the image, causing regions to spread into neighboring voxels and decreasing spatial resolution. Adjacent voxels can complicate surgical procedures due to their similar functions and shared blood supply. In such cases, spatial smoothing enhances the SNR and addresses functional anatomical variations that spatial normalization does not cover. Spatial smoothing is typically achieved by applying a Gaussian filter with a spatial constant. Users are required to specify the width in millimeters by utilizing the full width at half maximum (FWHM). The Gaussian kernel is a filter derived from a normal distribution curve [3].

6. FEATURE EXTRACTION TECHNOLOGY FOR NEUROLOGICAL DIAGNOSIS

Reducing massive datasets to a smaller set of feature vectors is the primary goal of feature extraction, which tries to extract more valuable information from the original signal. Feature extraction strategies are utilised when it is necessary to extract several features. Some of these approaches are described in the following section.

6.1. Discrete Wavelet Transform (DWT):

In the Discrete Wavelet Transform, the signal is divided into multiple subsets, with each frequency band represented by a time series of coefficients that capture its temporal evolution. These coefficients are organized into groups. By decomposing the signal into a set of wavelets, which are finite-length basis functions, it is possible to isolate features that vary over time. DWT is a multi-resolution analysis (MRA) because it allows for the simultaneous representation of time and frequency data. This technique is particularly useful for processing images across different frequency bands. Higher frequency bands capture the image's sharp edges, while the lower frequency band conveys the overall features. As a result, only the most relevant, or approximate bands are retained, while the others are discarded [27, 28].

6.2 Linear Discriminant Analysis (LDA)

Supervised learning uses Linear Discriminant Analysis (LDA) to lower the dimensionality. The objective is to reduce cluster fragmentation while increasing distance between them [29]. LDA works well for separating classes inside and amongst themselves. After assigning a uniformly distributed categorization parameter to each class, a single row is created for binary classification jobs from the remaining data. Maximising one of the many factors that dictate the projection approach is the goal of Fisher's linear discriminant, which seeks to maximise the ratio of variance across classes to variation within classes.

6.3. Principal Component Analysis (PCA)

A two-dimensional grid organizes standardised neuroimaging data from several places into the common space component of variables. Principal components are the building blocks of all neuroimaging data [2]. Principal component analysis (PCA) is an excellent tool for feature extraction and dimensionality reduction.It simplifies a large number of variables by using orthogonal transformations, focusing on linear combinations that carry the most information. PCA captures the greatest variability in the data, representing the most significant features of a dataset. Each of the n dimensions in the reduced n-dimensional representation of the original p-dimensional dataset is associated with an eigenvector, which forms the global covariance matrix [30].

6.4. Independent Component Analysis (ICA)

Separating signals into their constituent parts is the goal of Independent Component Analysis (ICA), a computer approach utilised in signal processing. We are able to achieve this by assuming that the subcomponents are non-Gaussian and statistically independent. ICA focuses on isolating independent signals from mixed sources. In neuroimaging analysis, ICA is crucial, particularly in separating spatial or temporal components. Spatial ICA is commonly used in MRI studies, while reports of brain activity in words are rare. ICA aims to divide coherent networks as distinctly as possible. However, because ICA separates all non-contiguous functional groups into independent components, the assumption of small areas can pose challenges. While ICA often uses ERP data, scalp data highlights the anatomical structures. Despite potential spatial overlap, ICA assumes time independence in its processing principles [38].

7. CLASSIFICATION ALGORITHM FOR NEUROLOGICAL DISEASE DETECTION

Independent Component Analysis (ICA) is a computational method used in signal processing with the aim of decomposing signals into their individual components. Assuming the subcomponents are statistically independent and non-Gaussian allows us to accomplish this.

7.1. Machine Learning Algorithms to Classify Neurological Diseases

A branch of artificial intelligence, machine learning is the process by which computers may learn new things on their own. Its ability to discover statistical patterns in massive datasets has led to its extensive use in domains like neuroscience. Because of its great accuracy and easy use, machine learning (ML) has recently become popular in illness diagnosis. ML also enables the prediction of neurological disorders (ND) through statistical analysis. Figure 2 illustrates the general data analysis or classification model that utilizes ML techniques. The following are examples of ML algorithms used to detect ND.

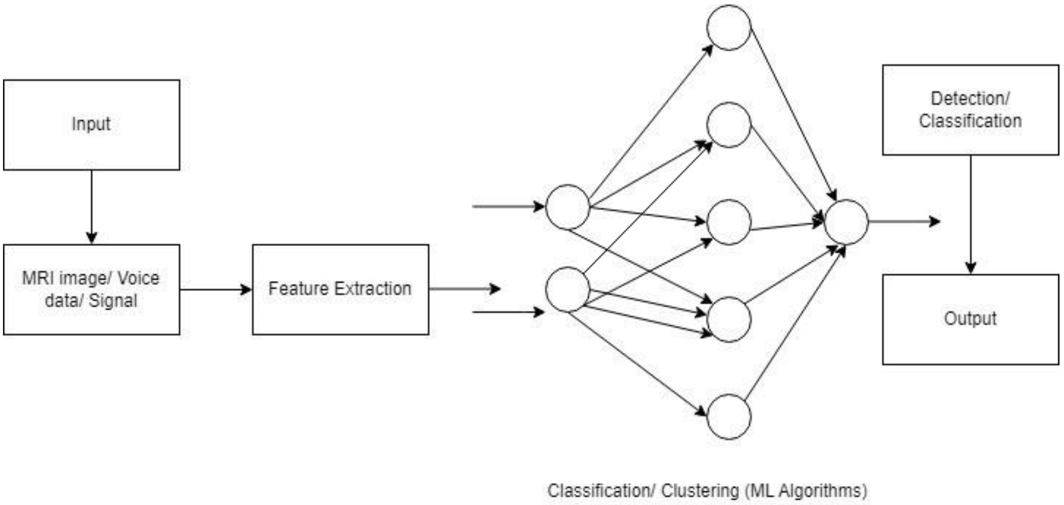

Figure 2: Diagram of General Machine Learning Structure [1].

Support Vector Machine (SVM) [11]: This method classifies data points by utilizing hyperplanes at different positions. The objective is to find a hyperplane that uses Support Vector Machines (SVM) to divide adjacent data vectors into two independent categories. One kind of vector that behaves like a plane is the support vector. SVM operates by employing data for training and testing functions. The training data is organized according to essential objectives and characteristics. The SVM model is subsequently constructed to forecast target values utilising the test data.

Gaussian Mixture Model (GMM) [33]: In both supervised and unsupervised learning settings, a Gaussian Mixture Model (GMM) can be used as a versatile tool. The data is shown as a combination of Gaussian distributions, with two main parameters—a mean vector and a covariance matrixfor each distribution. According to the model, the final density is just the sum of these Gaussian parts, with certain weights added in. The expectation maximisation (EM) algorithm is employed to detect error sites, generating a log-likelihood structure for the aggregated density. This is the basis for the model's conclusion after fitting the Gaussian mixtures.GMMs are widely used in biometric systems, such as speaker identification, due to their flexibility in modeling diverse distribution patterns. The capacity of GMM to zero in on particular characteristics of target images is a major strength of the method. When dealing with ND files that contain crucial audio data, GMM-based classification shines. There is hope for GMMs in the medical field as well.

Random Forest (RF) [11]: Random-forest models outperform decision trees by alleviating the problem of overfitting. These models consist of multiple decision trees, each bringing a unique perspective to the data. By using a method known as bagging, random forests combine the predictions of individual trees through majority voting. This approach reduces the risk of overfitting while maintaining the model's overall accuracy, ensuring reliable strength estimates from each tree.

Artificial Neural Network (ANN) [34]: Random-forest models are more effective than decision trees because they can prevent overfitting. These models consist of multiple decision trees, each offering a unique perspective on the data. Random forests use a method called bagging to pool the predictions of different trees and then use majority vote to integrate them. This method guarantees accurate strength estimations from every tree by lowering the probability of overfitting without compromising the model's overall accuracy.

7.2 Deep Neural Network Algorithms:

Machine learning systems, a branch of AI in computer science, can use deep learning as an advanced technique. Among the many applications of machine learning (ML), deep learning's ability to train models for feature extraction in high - dimensional spaces has been most noticeable in image analysis.A DL model used for picture analysis or classification can be seen in Figure 3, which shows its overall structure.

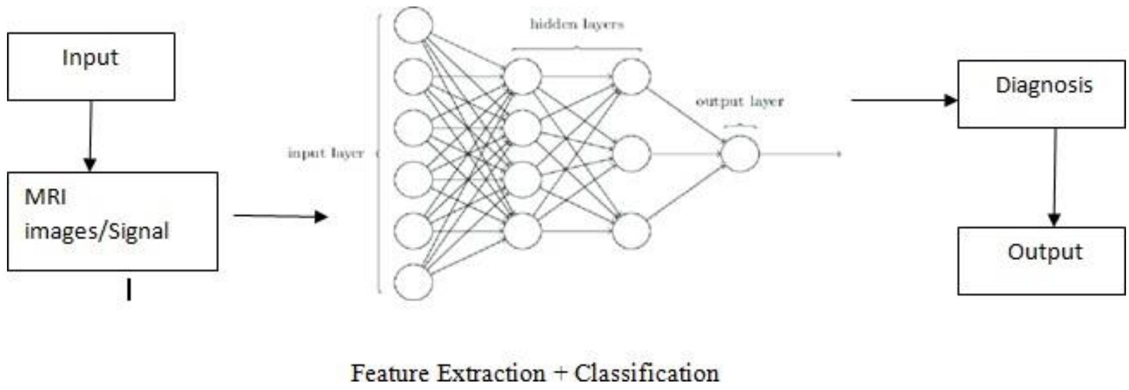

Figure 3: Diagram of General neural network structure [1]

Convolutional Neural Network (CNN): Image processing, pattern recognition and classification are just a few of the many common uses for convolutional neural networks (CNNs), whose architecture mimics how the human visual cortex operates. As a result, CNNs excel in ND classification, symptom detection, and magnetic resonance imaging (MRI) analysis. The convolutional layer filters input data without explicitly defining specifications through a kernel containing instructions. Layers are applied to sample feature maps, reducing size, computational complexity, and overhead [1]. CNNs, also known as ConvNets, typically process input images and use learnable weights to distinguish between them. Unlike standard matrix multiplications, CNNs perform convolution operations on at least one layer. This makes them particularly effective for processing images and videos in non-standard file formats. For sequence prediction of segmentation maps, 2D-CNNs utilize 2D convolution kernels. Various CNN architectures, such as LeNet, VGGNet, AlexNet, ResNet, GoogLeNet, and ZFNet, can be used to build models for MRI analysis [3].

Recurrent Neural Networks (RNN): Thesememory-driven models can utilize past information to inform present decisions. They consist of a series of identical sub-networks, each communicating with the next in a sequence. The hidden state is the key element of an RNN, retaining important information that helps generate the network's output. Since all inputs share the same parameters and processes to produce outputs, RNNs have a simpler architecture compared to other neural networks.RNNs are commonly applied in areas such as speech recognition, language modeling, image analysis, and annotation [35].

Long Short Term Memory (LSTM): Unlike LSTM networks, RNNs (Recurrent Neural Networks) use a different kind of memory. While RNNs can suffer from errors propagating and evolving over time, LSTMs are specifically designed to detect and prevent such issues. LSTMs use closed cells to store information outside of the standard RNN flow, functioning like a computer's memory by storing, retrieving, and updating data. LSTMs control the flow of information by opening and closing gates to decide what to store, when to read data, and when to modify it [3]. Gated Recurrent Units (GRUs) combine input and output gates into a single update gate, providing an alternate to Long Short-Term Memory (LSTM) techniques.Additionally, GRUs incorporates a reset gate, which decides how much information from the past to forget, as well as an update gate, which decides how much new information to store. Both of these gates are in addition to the previous one. The information that is sent to the output is controlled by these two gates, which are referred to as Reset and Update [1].

Deep Belief Network (DBN): In a network of connected graphs, a specific type of neural network known as a Deep Belief Network (DBN) makes use of both directed and undirected edges. All layers, except for the input layer, are hidden and span multiple levels. Each layer of a DBN, built from Restricted Boltzmann Machines (RBMs), communicates with the layers directly above and below it. RBMs serve as the fundamental building blocks of a DBN, and the communication between nodes across layers occurs with minimal distance. DBNs are used for processing, organizing, and analyzing images, videos, and motion capture data. Electroencephalography (EEG) is a particular clinical application that makes use of them; this method involves electrophysiological scanning of the brain to record its electrical activity [36].

Auto-encoder (AE): Autoencoder (AE) models are unsupervised machine learning models with identical inputs and outputs. They generate output by compressing the input into a latent representation, combining neural network capabilities for compression and decompression. Three primary components make up an AE: the encoder, the code, and the decoder. Two popular applications of AE networks in brain signal processing are feature extraction and dimensionality reduction[1]. The inner, hidden layer generates a code representing the input, while the encoder transforms the inputs into codes, and the decoder reconstructs the original input from those codes. There are three distinct types of AEs: sparse, denoising, and reduced AEs. Sparse AEs limit the number of active hidden nodes at any given time, which can restrict the model's responsiveness to training due to specific statistical characteristics. In contrast, denoising AEs are designed to filter out partial noise from the input and reconstruct the values that represent the true signal. Reduced AEs may involve adding a sharpness control to the loss function to enhance sensitivity to minor inconsistencies in the input [37].

Classification algorithms like Naive Bayesand Artificial Neural Networks (ANN), Support Vector Machines (SVM), can be employed to sort ND searches. These ML techniques can boost model performance throughout the early implementation phase by enhancing memory and catering to researchers' interests. However, these algorithms may not always be effective, especially with large datasets, indicating that real-time analysis of brain signals still requires the development of robust classification algorithms. Deep learning techniques like Long Short-Term Memory networks (LSTM), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Deep Boltzmann Machines (DBM) have simplified the process of learning and detecting neurological disorders. Meanwhile, researchers continuously refine deep learning models to better align with the brain's efficiency over time and data [1]. Regardless of the methodology and code used, the end goal of any machine learning or deep learning model is to answer a specific question using the data at hand in order to make comparisons easier.

8. UNRESOLVED CHALLENGES AND FUTURE DIRECTIONS

Despite significant progress in applying artificial intelligence (AI) for the diagnosis and early detection of neurological disorders (NDs), several critical challenges remain unresolved, limiting the widespread clinical adoption and efficacy of these systems.

8.1. Data Quality and Availability, Limitations and Biases

One of the primary limitations is the scarcity of high-quality, annotated datasets, especially for rare neurological conditions. Neurological data such as MRI, EEG, and voice recordings are often heterogeneous, collected across diverse devices and protocols, leading to inconsistencies in model training. Moreover, data privacy regulations restrict open sharing, further limiting access to large-scale, diverse datasets necessary for building robust AI models. Despite recent advancements in AI/ML for neurological disorder diagnosis, data-related limitations remain a fundamental challenge that impacts model generalizability, clinical relevance, and real-world applicability. Key issues include:

- Dataset Imbalance: Many public and proprietary datasets suffer from class imbalance, especially when rare neurological disorders (e.g., Huntington’s Disease or atypical parkinsonism) are underrepresented. This imbalance biases ML models toward more prevalent conditions, reducing diagnostic accuracy for minority classes.
- Underrepresentation of Demographic Subgroups: Neurological datasets often lack sufficient representation across ethnicities, age groups, and genders, leading to algorithmic bias. This results in variable diagnostic performance and raises fairness concerns in clinical deployment.
- Multi-Modality and Standardization Issues: AI models often combine imaging (MRI, PET, DaTSCAN) with clinical features. However, modality heterogeneity, inconsistent acquisition protocols, and differences in annotation standards hinder model comparability and transferability across institutions.
- Basic vs. Advanced Augmentation: While the manuscript initially referenced basic techniques and DCGANs, the field has moved towards more sophisticated synthetic data generation, such as StyleGANs, self-supervised learning, and federated learning frameworks. These allow for enhanced data diversity while preserving privacy and reducing over fitting. Future studies must prioritize robust data curation, multi-institutional validation, and bias auditing pipelines to mitigate these challenges.

8.2. Interpretability and Clinical Trust

Many AI models, particularly deep learning-based ones, function as "black boxes," offering limited interpretability. For clinical deployment, it is essential that models provide not just accurate predictions but also explainable outputs that can be understood and trusted by neurologists. The lack of transparency continues to pose a barrier to regulatory approval and clinician acceptance.

8.3. Data Limitations and Biases in Neurological AI Research

AI-based diagnostic tools in neurology are highly sensitive to dataset quality. However, most studies rely on small, imbalanced datasets that over represent common conditions while under representing rare or early-stage disorders (e.g., Multiple System Atrophy, Progressive Supranuclear Palsy). Class imbalance leads to poor generalization and bias in predictive performance. Moreover, there is minimal demographic diversity in popular datasets like ADNI or PPMI, making models less effective across age groups, ethnicities, or socioeconomic strata. Additionally, the lack of standardization across imaging modalities (MRI, PET, EEG) and acquisition protocols introduces variability, impairing model robustness. While basic augmentation methods and DCGANs are employed to address sample scarcity, they may not sufficiently capture real-world heterogeneity. Advanced strategies like transfer learning, federated learning, and synthetic data simulation using Style GANs or VAEs offer more scalable solutions. Integration of harmonization protocols and multi-center data collaboration is essential for training clinically viable models.

8.4. Integration with Clinical Workflows

Seamlessly integrating AI tools into real-world clinical workflows remains a challenge. Current solutions often require manual data input, are not interoperable with hospital information systems, or demand technical expertise that clinicians may lack. Real-time, user-friendly platforms with minimal disruption to existing practices are essential for practical adoption.

8.5. Ethical and Regulatory Challenges

The deployment of AI/ML systems in neurological diagnostics demands careful attention to ethical, legal, and societal implications (ELSI), Key concerns include:

- Patient Privacy & Data Governance: Neurological data, especially neuroimaging and genomic data, pose unique privacy risks. The concept of neuroprivacy emphasizes the potential for AI to infer sensitive traits (e.g., cognitive states, mental health risks), warranting stringent data anonymization, informed consent, and encryption protocols.
- Algorithmic Transparency and Bias: Black-box models may embed hidden biases, leading to diagnostic disparities. To address this, researchers advocate for explainable AI (XAI) and bias auditing frameworks to ensure equitable outcomes.
- Regulatory Frameworks: Clinical adoption of AI models requires compliance with regulatory standards like the FDA's Software as a Medical Device (SaMD) framework, European MDR, and Good Machine Learning Practices (GMLP). These emphasize the need for continuous post-deployment monitoring, real-world evidence, and risk-benefit analysis.
- Clinical Approval and Regulation: Models intended for clinical use must comply with medical regulatory frameworks. The FDA's Software as a Medical Device (SaMD) guidance and EU's MDR require models to undergo rigorous validation, auditing, and continuous post-market surveillance.
- Explainability and Trust: Clinicians require interpretable models to integrate AI tools into decision-making. Methods like saliency maps, LIME, and Shapley values are essential to validate predictions

To overcome these challenges and enhance the effectiveness of AI-based diagnostic systems, future research should focus on:

1. Federated and Privacy-Preserving Learning

Emerging techniques like federated learning can enable collaborative model training across institutions without the need to centralize sensitive patient data. This approach can help build more generalized models while preserving patient privacy.

2. Explainable AI (XAI)

Developing interpretable models that offer visual or statistical explanations for their predictions can foster trust and provide insights into disease mechanisms. Techniques such as attention maps, saliency analysis, and rule-based systems should be explored further in the context of neurological diagnosis.

3. Multimodal Data Fusion

Combining diverse data types—such as neuroimaging, genetic information, clinical notes, and sensor data—can significantly improve diagnostic accuracy and offer a holistic view of the patient's condition. Research should aim at designing architectures capable of learning from such complex multimodal datasets.

4. Lightweight and Mobile-Enabled Solutions

Future work should prioritize the development of lightweight, resource-efficient models suitable for deployment on mobile and edge devices. This is particularly valuable in remote or underserved areas where access to specialist care is limited.

5. Collaboration Between Disciplines

Advancing AI in neurology requires close collaboration between computer scientists, neurologists, ethicists, and regulatory experts. Interdisciplinary partnerships can ensure that technical innovations align with clinical needs and ethical standards.

9. CONCLUSIONS

The rise of high-speed computing and deep learning has greatly advanced the diagnosis and management of neurological disorders. This review summarizes key ML/DL methods, datasets, and imaging modalities used in current diagnostic tools. It also highlights essential preprocessing techniques that enhance model performance, offering a valuable resource for developing accurate and scalable AI-based diagnostic systems. Clinically, it underscores the potential of early detection methods in enabling timely treatment, which is crucial for slowing or preventing disease progression. Looking forward, this review can guide future research toward integrating diverse data modalities, exploring lightweight and real-time diagnostic systems, and developing embedded and mobile-based platforms (e.g., Android applications) for point-of-care use. Such innovations could revolutionize clinical workflows, particularly in low-resource settings, by making neurological screening more accessible, cost-effective, and accurate. This review underscores the transformative role of AI/ML in diagnosing neurological disorders, while critically evaluating systemic barriers related to data integrity, ethical safeguards, and clinical applicability. We advocate for more inclusive datasets, adherence to neuroprivacy principles, integration of multimodal signals, and rigorous regulatory alignment. Future systems should prioritize explainability, fairness, and clinical interoperability to translate research advances into real-world neurological care.

Abbreviations

PD	Parkinson’s Disease
AD	Alzheimer’s Disease
AI	Artificial Intelligence
ANN	Artificial Neural Network
AUC	Area Under the Curve
CAD	Computer-Aided Diagnosis
CHB-MIT	Children’s Hospital Boston - Massachusetts Institute of Technology
CNN	Convolutional Neural Network
CSF	Cerebrospinal Fluid
CT	Computed Tomography
DBM	Deep Boltzmann Machine
DBN	Deep Belief Network
DCGAN	Deep Convolution Generative Adversarial Network
DCT	Discrete Cosine Transform
DL	Deep Learning
DNN	Deep Neural Network
EEG	Electroencephalogram
ExMPLPQ	Exemplar Multiple Parameter Local Phase Quantization
FK-NN	Fuzzy K-Nearest Neighbors
FSL	FMRIB Software Library
fMRI	Functional Magnetic Resonance Imaging
FWHM	Full Width at Half Maximum
GMM	Gaussian Mixture Model
GRU	Gated Recurrent Unit
ML	Machine Learning
MMSE	Mini-Mental State Examination
MRI	Magnetic Resonance Imaging
MS	Multiple Sclerosis
ND	Neurological Diseases

OASIS	Open Access Series of Imaging Studies
OCT	Optical Coherence Tomography
PCA	Principal Component Analysis
IRE	Image Registration, Resolution, and Correction
PET	Positron Emission Tomography
PPMI	Parkinson's Progression Markers Initiative
RF	Random Forest
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
SPECT	Single Photon Emission Computed Tomography
SPM	Statistical Parametric Mapping
SS	Spatial Smoothing
SVM	Support Vector Machine
TF	Temporal Filtering
UPDRS	Unified Parkinson's Disease Rating Scale
WF	Wiener Filtering
LDA	Linear Discriminant Analysis

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Ethics

There are no ethical issues associated with this manuscript.

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